CHANGING WHAT'S POSSIBLE

Automating the Process of Invention

Fast Pitch

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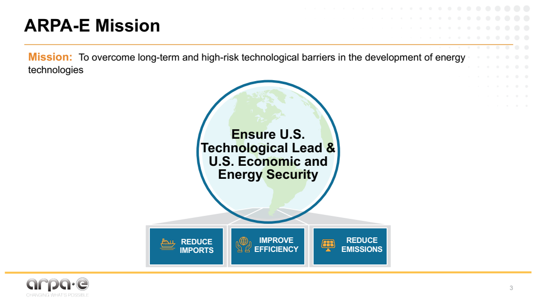
Automating the Process of Invention

*By leveraging the transformational potential of **machine learning (ML)***

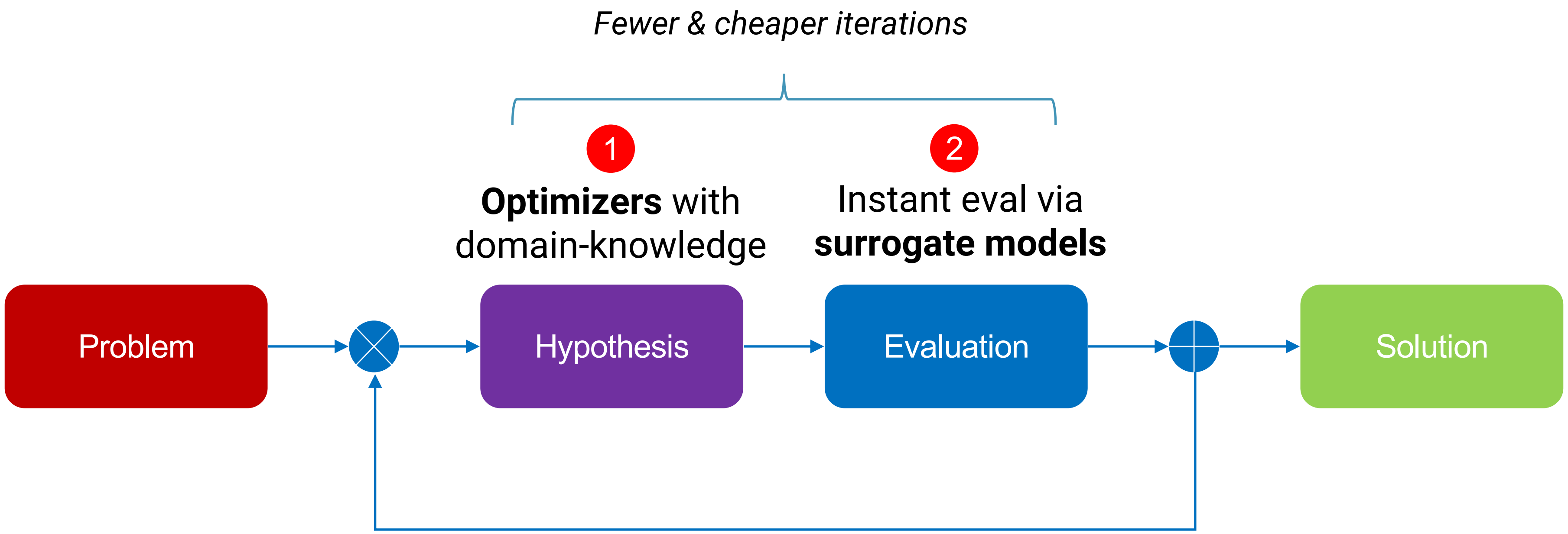
ML-Enhanced Design Tools → More Creative & **Productive** Engineers → Better Energy Products → Accelerated ARPA-E Mission



Today's Focus: Progress, Challenges & Potential Next Steps

Design Process Framework & Targeted Capabilities

***Goal**: Develop better technologies faster*



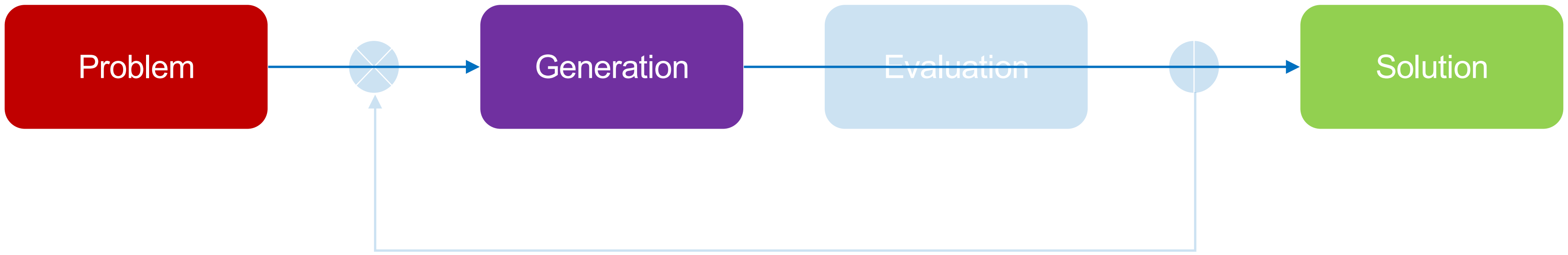
1 → Fewer iterations

2 → Faster evaluations

Design Process Framework & Targeted Capabilities

***Goal**: Develop better technologies faster*

3 Instant designs via **generative models**



3 → Get it right the first time

Progress: Domain Expert Optimizers

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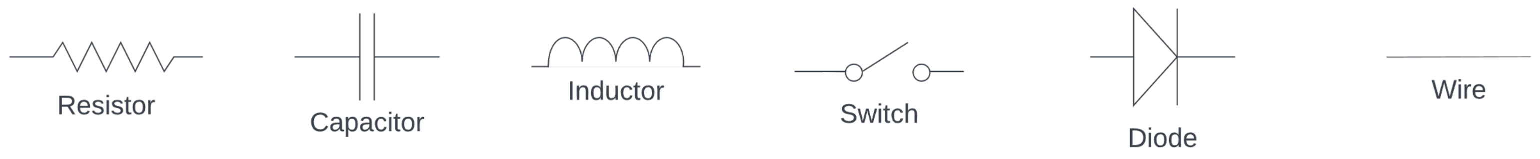
D' Focus Area: Combinatorial optimization of thermodynamic systems, <u>electrical circuits</u>, materials



Design questions

Which components? What specs? How connected? → Can we teach an algorithm to answer these questions?

D' Question

Yes, but … the world is complicated.

Circuit Design via Reinforcement Learning (RL)

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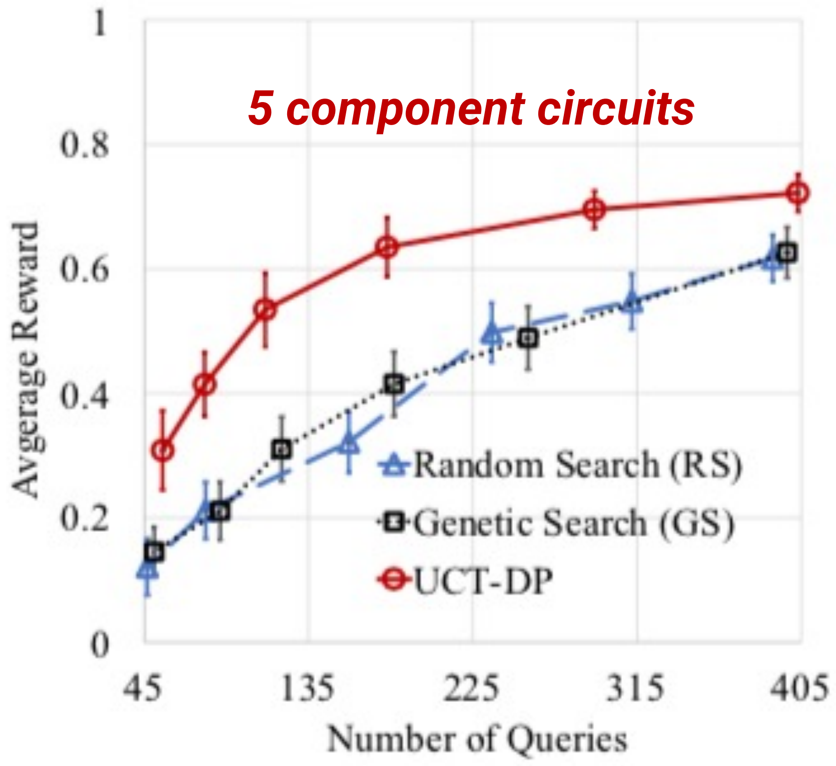
Learning Process

- Build & evaluate <u>many</u> circuit concepts
  - Components
  - Connections (Wires)
  - Controls (Switch Timing)
- RL algorithms learn to maximize “reward”
  - Efficiency
  - Cost
  - NPV

Examples

RL (UCT-DP) vs SOA



(a) Buck-Boost Converter

Fan et al, *From Specification to Topology: Automatic Power Converter Design via Reinforcement Learning*, ICCAD 2021.

Complexity Challenge: Combinatorial Explosion*

Lighthill, James, "Artificial Intelligence: A General Survey", **1973*

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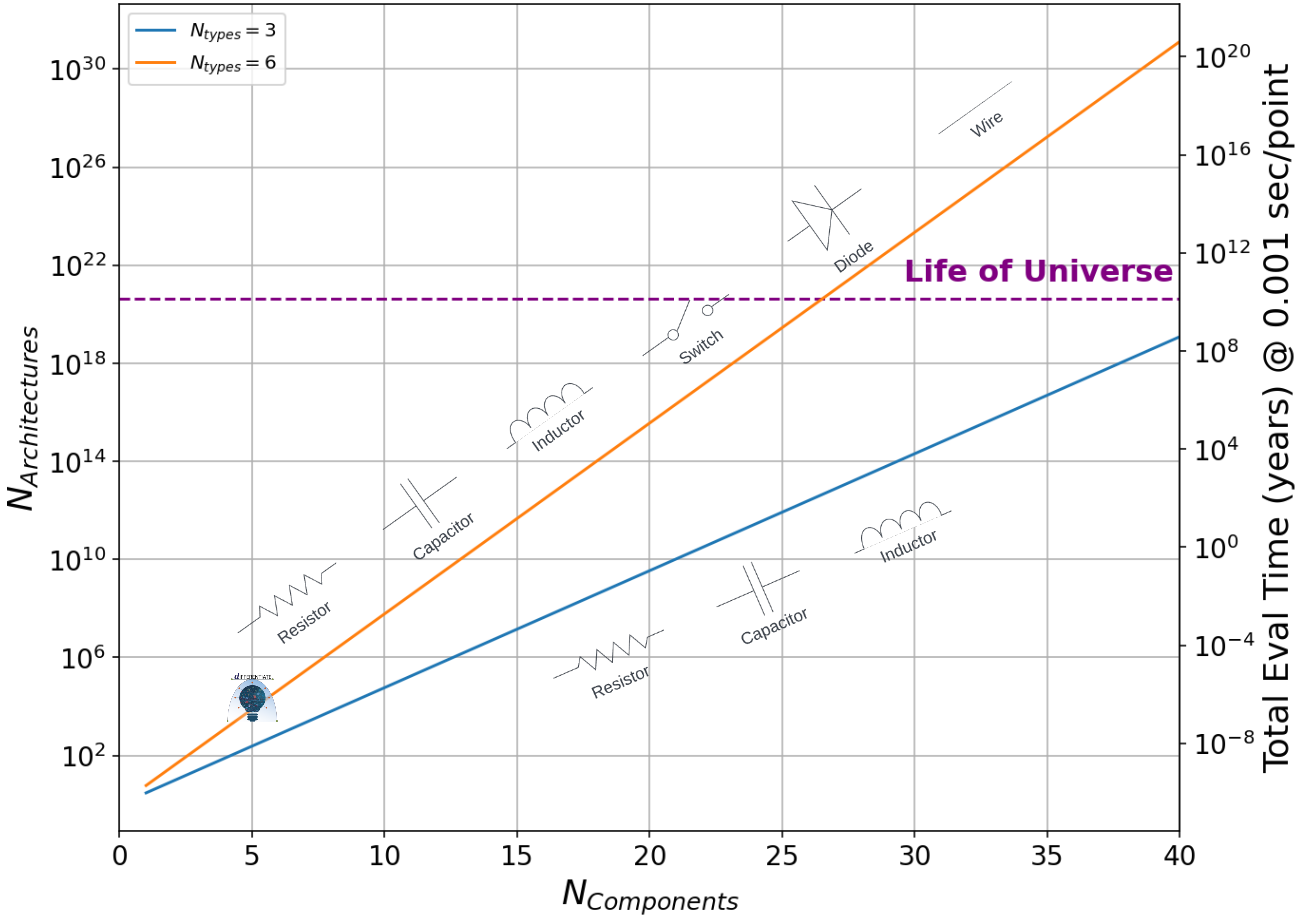
Enormous design space. *<u>Most</u> choices are bad.*

$$N_{architectures} = (N_{types})^{N_{components}}$$



High-Level Mitigations

1. *Learn to make good choices*
2. *Efficiently weed out bad ones*

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Emerging Complexity Management Solutions

1 2 3

DIFFERENTIATE

Goal: Reduce cost/amount of training data

- **Leverage existing knowledge**
  - Rules to enable rapid disposition of ‘bad’ ideas (e.g., no short circuits)
  - Structured algorithms (e.g., GNNs) that respect physics & architectures

- **Leverage existing data**
  - Historical data (good & bad)
  - Previously trained (NN) algorithms (transfer learning)

- **Focus on what’s important**
  - Dimensionality reduction

Takeaways

- ML methods offer potential for attractive design value propositions
  - **Domain expert optimizers**
  - Surrogate models
  - Generative/inverse models

- Challenge is management of ‘real-world-scale’ complexity
  - Leverage physics to simplify ML representations & reduce training cost
  - Learn when/how to transfer knowledge between applications/tools
  - …

- Ideas? Please reach out: *david.tew@hq.doe.gov*